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THE NATURE OF DIGITAL TECHNOLOGIES – DEVELOPMENT OF A MULTI-LAYER TAXONOMY

Research paper

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Abstract

Digitalization disrupts business models and smartifies products and services. Based on the ever-faster emergence and adoption of digital technologies such as the Internet of Things, blockchain, or augmented reality, digitalization irreversibly changes our private lives and organizational routines from all industries on a global scale. Thereby, digitalization develops unlimited potential in terms of innovation, connectivity, efficiency and productivity improvements. However, research and practice still lack a fundamental understanding of the nature of digital technologies. To address this gap, we developed a multi-layer taxonomy of digital technologies that includes eight dimensions structured along the layers of established modular architectures, i.e. service, content, network, and device. Based on our taxonomy, we also identified seven archetypes of digital technologies by means of a cluster analysis. To revise and evaluate our artefacts, we classified 45 digital technologies from the Gartner Hype Cycle of Emerging Technologies and conducted evaluation rounds with other researchers. Our results contribute to the descriptive knowledge on digital technologies. They enable researchers and practitioners to classify digital technologies on two levels of aggregation and to make informed decisions about their adoption.

Keywords: Digitalization, Digital Technologies, Taxonomy, Archetypes.

1 Introduction

Being the fastest development in human history, digitalization leads to comprehensive and ubiquitous change that affects individuals, economy, and the society (Fitzgerald et al., 2014; Gimpel and Röglinger, 2015). Digitalization is driven by the fast emergence and adoption of digital technologies (DTs). These technologies include emerging technologies such as the Internet of Things (IoT) or blockchain, but also more established technologies such as cloud computing or social media (Gartner Inc., 2017b). As for the IoT, for example, experts expect 50 billion smart devices to be installed and connected to the Internet by 2020, having a global economic impact of $7 trillion (Macaulay et al., 2015; Wortmann and Flüchter, 2015). Further, the volume of data is known to double every three years (Henke et al., 2016) and insights-driven businesses are predicted to take away $1.2 trillion per year from less-informed competitors by 2020 (McCormick et al., 2016). Besides the rapid growth of data and smart devices, an ever-faster commoditization and time-to-market of DTs is observable. Long-standing technologies such as the telephone required 75 years to reach 100 million users, whereas upcoming applications such as Instagram achieve the same coverage in little more than two years (Statista, 2017). Alongside the smartification of products and services, digitalization disrupts extant business models (Fitzgerald et al., 2014; Urbach and Ahlemann, 2016). For example, the world's largest accommodation and transportation providers, Airbnb and Uber, act as brokers and do not own any lodging or vehicles (McRae, 2015). In sum, DTs play a key role in the digital age. To exploit the economic and societal potential of digitalization, a big challenge is to understand the nature of DTs despite decreasing time-to-market and increasing variety.

Although the term technology is used intuitively, few is known about the nature of technologies (Arthur, 2009). Due to the slipperiness of the term (Kline, 1985), the literature lacks a generally accepted definition and either takes a context-oriented (Kline, 1985; Bain, 1937) or purpose-driven perspective (Arthur, 2009; Ferré, 1988). The opacity of technology also applies to immature DTs such as the IoT (Atzori et al., 2010; Püschel et al. 2016). Thus, the need for structuring the field of DTs has been discussed from various perspectives (Bharadwaj et al., 2013). From a high-level perspective, systemization approaches in the IS literature especially focus on IT ecosystems (Adomavicius et al., 2004) and different architectural models such as for cyber-physical systems (Horvath and Gerritsen, 2012). Besides, some works propose layered IS architectures for communication systems (Benkler, 2006) and Internet architectures (Farrell and Weiser, 2003; Solum and Chung, 2003). Coined by management consulting, the SMAC acronym provides some guidance structured along four technology groups *social*, *mobile*, *analytics*, and *cloud* (Frank, 2012). Although these high-level approaches consider various technologies, they do not enable a detailed classification of DTs. A detailed classification is necessary, as DTs cannot be confined to a few features. Providing deeper insights, low-level approaches address individual DTs. Thereby, a shift towards well-elaborated taxonomies can be observed. Such taxonomies shed light on properties of smart things (Püschel et al. 2016), big data algorithms (Fahad et al., 2014), mobile media (Scolari et al., 2012), business-to-thing interaction patterns (Oberländer et al., 2017), or cloud computing (Keller and König, 2014; Rimal et al., 2009). In addition, the economic potential of digital services (Williams et al., 2008) and digital business models (Bock and Wiener, 2017) are subject of discussion. Although these contributions provide rich insights, they focus on individual DTs. Thus, they are not suitable to classify DTs per se. Regarding the challenges of accelerating development cycles and market movements, there is a substantial need for structuring the field of DTs (Bharadwaj et al., 2013). Against this backdrop, we investigate the following research question: *How can digital technologies be classified?*

To answer this research question, we propose a multi-layer taxonomy in line with the taxonomy development method as per Nickerson et al. (2013) and established DT architectures (Yoo et al., 2010). Our taxonomy builds on an extensive literature review, which was iteratively refined and extended based on empirical evidence and discussions with fellow researchers. We validated the applicability of our taxonomy by classifying 45 real-life objects drawn from the Gartner Hype Cycle of Emerging Technologies (GHC). Based on our taxonomy, we also strived for higher-level insights by using hierarchical clustering, which resulted in seven archetypes. In a consecutive step, we verified the validity and reliability of the clustering by applying the Q-sort method. With our taxonomy and archetypes at hand, researchers and practitioners can understand the nature of DTs, enhancing the transparency within this rapidly changing field. In addition, managers and product owners can leverage our taxonomy to make informed decisions about the adoption of distinct DTs. From an academic perspective, our work adds to the descriptive knowledge on DTs.

Our study is structured as follows: In Section 2, we define DTs that fit our purpose of being classified by a taxonomy. In Section 3, we outline our research method for developing our taxonomy in accordance with Nickerson et al. (2013). In Section 4, we describe the dimensions and characteristics that form our taxonomy. In Section 5, we introduce the seven archetypes of DTs derived from a cluster analysis. In Section 6, we compile selected evaluation results. We conclude by summarizing our results, limitations, and suggestions for future research in Section 7.

2 Theoretical Background

2.1 The nature of technology

The digitalization of products and services, i.e. the adoption and usage of emerging technologies in individual, organizational, and societal contexts (Legner et al., 2017), is a fast-moving global megatrend that impacts all industries (Collin, 2015). Besides the transformation of business models or the enabling of new value creation opportunities (Gartner Inc., 2017a), digitalization helps to improve work practices in an explorative or exploitative way (Denner et al., 2017; Rosemann, 2014). As the fast emergence of technologies is a central driver of digitalization, today's scientific and professional literature describes a broad spectrum of DTs within different academic disciplines or contexts, e.g. digital, nano, biological, or neuro technologies (Quindazzi, 2017). Besides these different perspectives, a common understanding of the term technology is missing. Even in the IS literature, where researchers investigate the effects of established and emerging information technologies (IT), the term remains fuzzy. Accordingly, we first structure the broad field of technologies by investigating its fundamental nature, building a shared understanding for the purposes of our research that enables discussing technologies in general and to decide which DTs fit our purpose of being analysed in terms of our taxonomy.

Professional literature presents numerous definitions of technologies in a practical sense. Jing (2006), for instance, describes IT as a variety of technologies involving the gathering, processing, transmission, storage, and display of information. Zuppo (2012), in contrast, focuses on information and communication technologies, defining them as technologies that facilitate the transfer of information and various types of electronically mediated communication. As soon as one broadens the perspective, the understanding of technology gets less tangible, as the exemplary definition of technologies as “all tools, machines, utensils, weapons, instruments, housing, clothing, communicating and transporting devices and the skills by which we produce and use them” (Bain, 1937, p. 860) illustrates. According to Arthur (2009), a discussion on technologies and their fundamental understanding is missing. Ferré (1988) points out that the term inherits a certain ambiguity, mainly caused by its broad field of application in different contexts. Kline (1985) describes this phenomenon as “slipperiness” that results from using the term technology for things, actions, processes, methods, and systems alike. Trying to address this problem, Arthur (2009) examines the fundamental nature of technologies and proposes three definitions: (1) technology as a means to fulfil a human purpose, (2) as an assemblage of practices and purposes, and (3) as the entire collection of devices and practices available to a culture. Arthur further postulates the theory of “combinatorial evolution”, arguing that each technology component is a miniature technology itself and all technologies exploit some effect or phenomenon, usually several. In sum, depending on the context, technologies range from abstract ideas to highly specialised devices with defined functionalities.

To structure the broad field of technologies and to develop a taxonomy that supports understanding the nature of DTs, we had to focus our investigations on a unified level of granularity. Building on the seminal ideas of Arthur (2009), we thus introduce a framework that groups technology into three layers. As shown in Figure 1, the differentiation follows the profound ideas introduced above: Technologies are always organised around central principles (i.e. the essential ideas geared to fulfill a human purpose), which then need to be implemented in forms of physical components. Building the most abstract layer of our framework, concepts comprise multiple principles and a great variety of technical implementations without preferring a certain one (e.g. propulsion technology following contextual principles geared towards any kind of movement). Differing from technology concepts, the intermediate layer – for reasons of simplification just called *approach* – is always based on one principle although different practical implementations may have individual focuses (e.g. a jet engine following the principle of burning fuel to move an aircraft). Finally, the layer of physical components refers to a specific function built to fulfill a predefined task (e.g. a fuel supply system that drives a jet engine). These components are the main assemblies of a technology carrying out its basic function and related sub-assemblies (Arthur, 2009). Multiple physical components with the same principle can be allocated to one specific approach (1:n relation). In contrast, it is possible to associate an approach with multiple concepts, and vice versa (n:m relation). As concepts do not pre-determine the form of implementation, the realization of the principle is independent. An approach might be used in different concepts, especially as digitalization allows the application in a steadily growing number of use cases and domains.

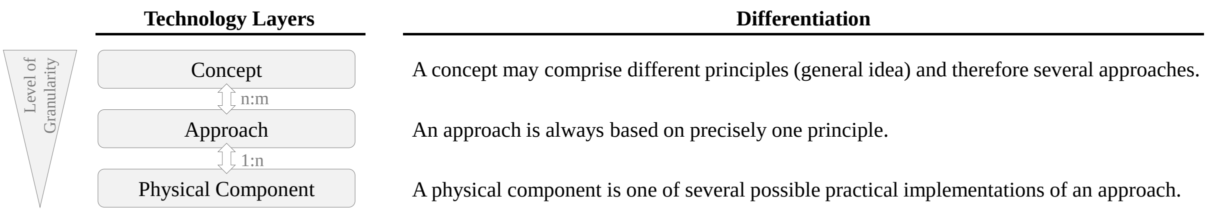

Figure 1. Layers of Technology

2.2 The specifics of digital technology

Finding a sound definition for the term DT, i.e. a specific subset of technologies, turns out to be even harder than for technology itself. Although many contributions deal with the general idea of technologies in a digital context, the term is not consistently defined (Denner et al., 2017). According to Loebbecke (2006), DTs comprise all technologies for the creation, processing, transmission, and use of digital goods that can be summarised under the term information, communication, and media technologies. Fitzgerald et al. (2014) understand DTs simply as social media, mobile, analytics, or embedded devices. Applying a similar approach, the SMAC acronym classifies DTs into Social, Mobile, Analytics, and Cloud technologies (Ackx, 2014; Evans, 2016; Uhl et al., 2016). Just like Arthur (2009) did in terms of technology, Yoo et al. (2010) had a look at DTs in a broader context. They argue that DTs differ from earlier technologies in three characteristics: (1) re-programmability that separates the functional logic of a device from its physical embodiment, (2) homogenization of data that allows for storing, transmitting, and processing digital content using the same devices and networks, and (3) the self-referential nature yielding positive network externalities. Finally, Yoo et al. (2010) propose a modular architecture for DTs, consisting of the four layers service, content, network, and device (see Section 4 for details).

To define DTs that fit our purpose of being analysed in terms of a taxonomy, we refer to the different layers of technology (i.e. concepts, approaches, and physical components) from the framework introduced above. As a subset of technologies, the framework also applies to DTs. Accordingly, we state that concepts of DTs refer to multiple principles, which – in this specific subset – usually strive for the usage of digital resources (e.g. IT infrastructure) to effectively find, analyze, create, communicate, or use information in specific contexts (NZCETA, 2017). Smart home, for instance, is a concept that includes DTs such as indoor climate control or in-house security, all geared towards different purposes and following different principles. As for the second layer of our framework (i.e. approaches), augmented reality can be used as example: following the principle of digitally enhancing users' interaction with the environment, manifold devices and forms of data usage/presentation (e.g. text, graphic, and audio) appear (Gartner Inc., 2017a). The lowest layer of our framework (i.e. physical components) can be exemplified using volumetric displays as example, which create visual representations of objects in which the image changes as the viewer moves (Gartner Inc., 2017a). As outlined above, DTs on this layer differ from other technologies in uniting the special characteristics of re-programmability, homogenization of data, and a self-referential nature (Yoo et al., 2010). Against this backdrop, the development and application of our taxonomy, which we present below, strictly focuses on DTs on the 'approaches' layer of our framework. Examples are 4D Printing, Augmented Reality, Blockchain, or Smart Dust.

3 Research Method

3.1 Developing a taxonomy for digital technologies

For our purposes, the taxonomy development is the appropriate method to structure the complex field of DTs. Also referred to as framework or typology, a taxonomy describes a classification scheme for clustering objects based on common characteristics (Nickerson et al., 2013). In addition, taxonomies enable researchers and practitioners to understand, analyse, and organise knowledge from specific domains (Nickerson et al., 2013). As there is a substantial need for fostering transparency and clarity, these attributes are particularly appropriate for structuring the highly dynamic field of emerging and disruptive DTs (Manyika et al., 2013).

In this paper, we applied the iterative taxonomy development method as per Nickerson et al. (2013). Initially, the multi-step process demands for the determination of a meta-characteristic, which represents the main purpose of the taxonomy to distinguish among the objects of interest (Nickerson et al., 2013). Combined with the determination of objective and subjective ending conditions, the prerequisites are set to choose an approach per iteration, i.e. conceptual-to-empirical or empirical-to conceptual. Within the taxonomy development process, Nickerson et al. (2013) allow for combining both approaches. The conceptual-to-empirical approach conceptualises dimensions and characteristics of the taxonomy. To do so, dimensions are conceived deductively based on the researchers' creativity and justificatory knowledge. After assigning objects to the dimensions and characteristics, an initial or revised taxonomy is obtained. The empirical-to-conceptual approach identifies a subset of objects first. In a consecutive step, these objects are grouped and dimensions as well as characteristics are inferred inductively. Once again, this approach results in an initial or revised taxonomy. After each iteration, it must be checked whether the ending conditions are met. The taxonomy development process continues until all predefined ending conditions are met.

Our taxonomy development process is based on four iterations. Considering the immature and highly dynamic field of DTs, we chose the conceptual-to-empirical as well as the empirical-to conceptual approach to aim for a sound and applicable taxonomy. We started the taxonomy development process by setting the meta-characteristic. In line with our research question, we aimed to *structure characteristics of DTs along the modular architecture for DTs* as per Yoo et al. (2010). Following Nickerson et al. (2013), we adopted the following predetermined objective ending conditions: (1) each characteristic is unique within its dimension, (2) each dimension is unique and not repeated within the taxonomy, and (3) at least one object must be identified per characteristic and dimension. Furthermore, Nickerson et al. (2013) require characteristics to be mutually exclusive per dimension. During the taxonomy development process, however, we experienced that for some dimensions it is infeasible to restrict the choice of characteristics to be mutually exclusive as relevant information would be lost. In line with other recently published taxonomies, we therefore allow for non-exclusive characteristics (Jöhnk et al., 2017; Püschel et al., 2016). Supplementing our objective ending conditions, we also chose two subjective ending conditions, which are met if (1) an iteration does not imply further modification of the taxonomy, and (2) the authors agree that the taxonomy is concise, robust, comprehensive, extendible, and explanatory (Nickerson et al., 2013).

Due to a missing common understanding of the term DT, we decided to start the *first iteration* with the conceptual-to-empirical approach. Therefore, we conducted an extensive literature review with a broad scope, ranging from very concrete technologies like volumetric displays to more abstract and general concepts like smart robots. This led to a superset of layers, dimensions, and characteristics, comprising first distinctive features of DTs and building the foundation for the following iterations.

To enhance our taxonomy's structure, we continued the development process by applying the empirical-to-conceptual approach in the *second iteration*. In line with Gregor (2006), Williams et al. (2008), Tsatsou et al. (2010), and von Briel and Schneider (2012), we challenged the layers, dimensions, and characteristics of our taxonomy through the following iterations by classifying real-life objects (i.e. concrete DTs) in a bottom-up manner and we adjusted the taxonomy accordingly. Instead of aiming for an exhaustive examination, we tried to cover the broad variety of DTs by choosing a sample on the basis of the commonly known GHC from the last three years (Gartner Inc., 2015, 2016, 2017a). The GHC fits our needs very well as it encompasses many DTs from various domains and development stages, ranging from hyped blueprint ideas to established technologies. Moreover, the observation of three consecutive years resulted in a manageable and sound sample size of 64 identified DTs. However, to guarantee comparability among these DTs, we reduced the number of objects according to the following criteria: (1) the definition of the DT must be comprehensible and provide sufficient information for classification, (2) the DT must comply with our definition of an approach (Section 2), which, for instance, does not apply to the concept of Smart Workspace as it comprises multiple different ways to improve working, and (3) the DT must be different from any other DT; if this did not apply, we merged respective DTs, e.g. Augmented Data Discovery and Smart Data Discovery. The adjusted sample included 45 DTs (Figure 2). Throughout the following iterations, the sample was classified by two co-authors independently from each other, solely using information from the GHC.

As the revised taxonomy did not meet our subjective ending conditions, we conducted a *third iteration*. Following the empirical-to-conceptual approach again, we additionally validated our taxonomy by conducting two focus group meetings among academics with an IS background. For this purpose, we asked the participants to classify each DT from a given sample. Thus, we shared instructions, including a detailed description of the taxonomy, DT definitions from the GHC, and an overview of all DTs to be classified. The sample comprised ten DTs and was compiled according to the following criteria: (1) at least two DTs for every characteristic must be included, and (2) the sample must be a proper subset of the 45 DTs used in the second iteration. After all participants had completed the classification, we discussed classification problems and suggestions for improving the taxonomy with the participants. Each focus group meeting had a total duration of 75 minutes and was hosted by two co-authors. The focus groups encompassed eight and 20 participants, consisting of professors, doctoral students, and students from two different universities. After each evaluation round, we analysed the findings quantitatively and qualitatively (e.g. by calculating hit ratios) and refined the taxonomy accordingly.

YEAR	DIGITAL TECHNOLOGIES * **
2017	4D Printing, 5G, Augmented Data Discovery (Smart Data Discovery), Augmented Reality, Autonomous Vehicles, Blockchain, Brain Computer Interface, Cognitive Expert Advisors, Commerical UAVs (Drones), Conversational User Interfaces, Deep Learning, Deep Reinforcement Learning, Digital Twin, Edge Computing, Enterprise Taxonomy and Ontology Management, IoT Platform, Machine Learning, Neuromorphic Hardware, Quantum Computing, Serverless PaaS, Smart Dust, Virtual Assistant, Virtual Reality.
2016	802.11ax, Affective Computing, Data Broker PaaS, Gesture Control Device (Gesture Control), Natural-Language Question Answering, Virtual Personal Assistant.
2015	3D Bioprinting Systems for Organ Transplant, Advanced Analytics with Self-Service Delivery, Autonomous Field Vehicles, Bioacoustic Sensing, Biochips, Citizen Data Science, Cryptocurrencies, Cryptocurrency Exchange, Consumer 3D Printing, Enterprise 3D Printing, Hybrid Cloud Computing, IoT, People-Literate Technology, Smart Advisors, Speech-to-speech Translation, Wearables.

* DTs within more than one GHC are listed for their most recent appearance ** DTs in brackets present similar terms for different years

Figure 2. Adjusted Sample of 45 Digital Technologies from the Gartner Hype Cycle

As the first subjective ending condition (i.e. no further modifications) was not met in the previous iteration, we applied the empirical-to conceptual approach also in the *fourth iteration*. Once more, we repeated the classification procedure by reassigning the identified DTs to dimensions and characteristics of our taxonomy. With only marginal modifications of the taxonomy, we agreed to have met the first subjective ending condition. Further, all objective ending conditions were met as well and all authors agreed on the taxonomy being concise, robust, comprehensive, extendible, and explanatory (Nickerson et al., 2013). Thus, we decided to refrain from another iteration and finished the taxonomy.

3.2 Deriving archetypes of digital technologies

With the taxonomy development process revealing first indications of correlations among the characteristics of DTs from the GHC, we also strived for higher-level insight. Thus, we applied cluster analysis to identify DT archetypes. This statistical technique groups objects with similar characteristics (Field, 2013; Hair et al., 2010). It aims for a high degree of homogeneity within each cluster and a high degree of heterogeneity between different clusters (Bacher et al., 2010; Backhaus et al., 2011; Cormack, 1971). For our purposes, we used the agglomerative hierarchical clustering algorithm by Ward (1963), as it is often applied in practice (Backhaus et al., 2011; Ferreira and Hitchcock, 2009; Saraçli et al., 2013). In contrast to partitioning clustering algorithms, which assign objects to a predetermined number of clusters until the objective function reaches an optimum, hierarchical algorithms merge or divide clusters to generate solutions for all possible numbers of clusters before choosing the desired cluster amount (Backhaus 2011). As distance measure, we chose the Manhattan-metric, which is an established and straightforward approach that can deal with nominally scaled dimensions, proved useful in combination with the Ward algorithm (Strauss and Maltitz, 2017), and has been applied in many use cases, e.g. Ross and Wolfram (2000) and Romero et al. (2015). In accordance with Bacher et al. (2010), we dichotomised the classification of DTs such that every characteristic is represented by a separate column and assigned 1, if the respective characteristic is observable, and 0, otherwise. We then standardised each dimension's maximum possible distance between two DTs to 1 to ensure an equal weighting of all dimensions. To conclude our cluster analysis, we determined the suitable number of clusters. Despite literature offering a great variety of related measures, there is no agreement on one best approach (Wu, 2012). The disagreement is also reflected in our calculation of twelve different measures, which left us with no clear guidance as the appropriate number of clusters ranged between two and 14. Hence, we followed the idea of balancing the trade-off between homogeneity within each cluster and the manageability of the cluster solution (Backhaus et al., 2011; Milligan and Cooper, 1985; Sneath and Sokal, 1973). After we agreed that the DTs of each derived cluster are sufficiently homogenous and adequately describe the corresponding archetype, we completed the agglomeration process. At the same time, we secure manageability by ensuring interpretability and meaningfulness of each cluster. In sum, we ended up with seven DT archetypes.

After we completed our taxonomy and derived the archetypes, we validated both artefacts. For our taxonomy, we determined its reliability via dimension- and object-specific hit ratios and prepared additional descriptive statistics to validate its applicability. The hit ratios measure the authors' agreement regarding the classification of the 45 DTs from our sample (Nahm et al., 2002), whereby the assigned values range from 1 for perfect agreement to 0 for disagreement at all. Partial agreement is expressed via intermediate values. The descriptive statistics comprise the calculation of absolute and relative ratios to ensure comparability among exclusive and non-exclusive dimensions. The absolute ratios describe the relation between the number of observations per characteristic to the total number of objects. As for non-exclusive dimensions, we further calculated the relative ratio, which relates the number of observations per characteristic to the total number of observations per dimension.

To evaluate our archetypes' usefulness, we applied the Q-sort method. Frequently being used to test taxonomies (Carter et al., 2007; Oberländer et al., 2017; Rajesh et al., 2011), this statistical tool examines peoples' attitudes and opinions (Stephenson, 1935) and has already been applied in various fields (Thomas and Watson, 2002). For our purposes, we follow the principles by Nahm et al. (2002), according to which reliability and validity of our archetypes are measured based on the agreement between two judges. In our study, one author first performed cluster analysis to identify archetypes within 45 DTs drawn from the GHC. In a second step, two other co-authors classified the DTs. According to Carter et al. (2007), all co-authors met the requirements to perform the Q-sort, as we gained deep insights into the area of interest during taxonomy development. After completing the classification, we measured the archetypes' reliability. Cohen's Kappa Coefficient (Cohen, 1960), which is defined as "the proportion of joint judgement in which there is agreement after chance agreement is excluded" (Nahm et al., 2002, p. 115). Considering the frequency of correctly assigned objects, validity is measured through object-specific and overall hit-ratios (Moore and Benbasat, 1991). Section 6 summarises our evaluation results.

4 A Multi-Layer Taxonomy of Digital Technologies

In this section, we present the layers, dimensions, and characteristics of our taxonomy, including examples of real-life objects from the GHC. To ensure consistency across the taxonomy and to gain a deeper understanding of the nature of DTs, we took the perspective of an individual DT. Therefore, our taxonomy encompasses four layers and eight dimensions (Figure 3). Except for the content layer, the characteristics of all dimension are mutually exclusive.

To determine suitable layers for the taxonomy, we analysed extant architecture models that describe systems and infrastructures on a high level of abstraction (Horvath and Gerritsen, 2012). In line with our research question, this holistic view facilitates the classification of complex DTs. Regarding the field of digital infrastructure, extant models comprise technology roles in digital ecosystems (Adomavicius et al., 2004), a three-layered concept of digital ecosystems (Benkler, 2006), and an architecture model for cyber-physical systems (Horvath and Gerritsen, 2012). From a more IoT-centric perspective, similar technology stacks were proposed by Porter and Heppelmann (2014), Fleisch et al. (2014), and Borgia (2014). Based on the works of Adomavicius et al. (2004) and Benkler (2006), we follow the layered modular architecture as proposed by Yoo et al. (2010) and structure the dimensions of our taxonomy along the layers service, content, network, and device. To foster clarity and readability, we ordered these layers from service aspects to technical matters.

Starting from a technical perspective, the *device layer* accounts for a DT's need for underlying devices to execute their functionalities. Widening the focus on physical devices (Benkler, 2006) through the inclusion of logical capabilities, Yoo et al. (2010) divide this layer into physical machinery (e.g. computer hardware) and logical capabilities (e.g. operating system). We account for this distinction by covering the role of technology supplemented by the disclosure of a DTs acting focus within its ecosystem.

To describe a DT's interaction with its socio-technical environment in more detail, we included the *network layer*. According to Yoo et al. (2010), a network is characterised by physical transport (e.g. cables) and logical transmission (e.g. network standards). For our purposes, we included the direction of information flow and the number of entities involved. Transferred via networks, data is a key resource for all DTs. Besides describing received and provided data, the *content layer* specifies how data is used and processed. Finally, the *service layer* captures the purpose of DTs by referring to its application functionality (Arthur, 2009). In our work, we differentiate between the extent of human involvement and the purpose of a DT. After finishing the taxonomy, however, we abandoned the main principle dimension in favour of striving for higher-level insights by means of archetypes.

LAYER	DIMENSION	CHARACTERISTIC					EXCLUSIVITY*
Service	Human Involvement	Active Usage	Passive Usage				ME
Content	Data Treatment	Collection	Aggregation	Analysis	Execution	Transmission	NE
	Input	Digital	Physical				NE
	Output	Digital	Physical				NE
Network	Multiplicity	One-to-One	One-to-Many	Many-to-Many			ME
	Direction	Uni-directional	Bi-directional				ME
Device	Role of Technology	Application	Infrastructure				ME
	Scope	Cyber	Cyber-Physical				ME

* *ME: Mutually Exclusive; NE: Non-Exclusive*

Figure 3. Multi-layer Taxonomy of Digital Technologies

4.1 Device layer

Every DT is bound to specific devices, which might be the core of a DT or only represent the underlying hardware, whereas the software is not necessarily determined to use a specific predefined infrastructure. To account for the trend of DTs increasingly using undetermined devices, our dimensions deal with the *role of technology*, meaning its function either being a valuable stand-alone technology or enabling the application of other DTs, and it's acting focus (*scope*).

Adomavicius et al. (2004) claim the role of a technology to be essential for understanding its function within the ecosystem under consideration. Therefore, *application* technologies provide a set of functions that directly address and satisfy users' needs. Examples offer a broad spectrum of applications, ranging from Machine Learning over Smart Advisory to various human-machine interfaces (HMIs). *Infrastructure* technologies, in contrast, build the foundation for applications and add value by supporting, enabling, and enhancing their functionality. Neuromorphic Hardware or platform solutions such as Hybrid Cloud Computing are representatives of this characteristic. In contrast to Adomavicius et al. (2004), we refrain from including a component characteristic. In line with Arthurs' (2009) re-combinatorial idea on the evolution of technology, components (i.e. technological subunits) are combined to form higher-level technologies. However, as stand-alone technologies may become components or exist in both forms, the definition of component leaves unnecessary room for interpretation and is not independent from the point in time where the classification took place. Hence, it does not meet our subjective ending condition of developing a robust taxonomy.

Besides a DT's role in digital ecosystems, the device layer provides information about the acting focus of a device. In line with major contributions on cyber-physical systems, we distinguish between a *cyber* and *cyber-physical* scope (Acatech, 2011; Broy et al., 2012; Horvath and Gerritsen, 2012; Zamfirescu et al., 2014). The cyber scope refers to the idea of a technology whose acting focus is located within the digital world only. Typically, platforms, networks, and analytical technologies without HMIs feature this characteristic. Following Horvath and Gerritsen (2012), we also include non-digital computing technologies such as Quantum Computing. A cyber-physical focus, in contrast, is characterised through its influence on the physical environment. For instance, Virtual Reality changes the way a human perceives its environment. In a former version of our taxonomy, we additionally listed a purely physical focus. In our focus group meetings, however, there was broad consensus that DTs always include a cyber element. Thus, we dropped this characteristic.

4.2 Network layer

Also referred to as transmission (Borgia, 2014) or connectivity (Fleisch et al., 2014), a network captures information exchange between involved entities (Bucherer and Uckelmann, 2011). Thinking of a network as an arrangement of nodes and edges, *multiplicity* provides information on the number and order of nodes, whereas the term *direction* characterises the edges between them.

Accordingly, the 'direction' dimension describes the information flow among entities that exchange data. Similar to a one-way-street, a *uni-directional* information flow limits the exchange of data to one direction. Examples comprise, inter alia, sensor technologies, which solely generate and forward information (e.g. Smart Dust), but also DTs which receive and process information without sending information in return (e.g. 4D Printers). In contrast, a *bi-directional* information flow allows for information to be exchanged in more than one way between the entities involved. Thereby, the sequence and direction of the information flow is not predetermined. This applies, in particular, to DTs with HMIs, freely communicating and interacting with users, e.g. Natural Language Question Answering (NLQA).

Widening the entity definitions for human-computer interaction by Porter and Heppelmann (2014) and Püschel et al. (2016), we distinguish between three human-technology or technology-technology interaction patterns and point out the number of and the relations among entities involved. For a *one-to-one* interaction, the number of participants is limited to two entities only, whereas an entity is not necessarily restricted to an individual, but a group of similar entities. This applies to many DTs with interfaces to the physical world, such as Augmented and Virtual Reality. The *one-to-many* interaction implements the idea of a hub, building a central system connected to several entities simultaneously. Hybrid Cloud Computing, for example, enables a large number of users to meet and exchange data on a central platform. The most complex interaction form is a *many-to-many* interaction, in which the underlying technology connects all participating entities with one another. Notable examples are wireless networks like 802.11ax or next-generation cellular standards such as 5G, which aim for supporting a growing number of devices at ever-faster transmission rates.

4.3 Content layer

With data being the key resource for DTs, it is essential to understand how DTs receive (*input*) and provide (*output*) data, and furthermore how this data is used and processed (*data treatment*).

Within a taxonomy of smart things, Püschel et al. (2016) analyse data treatment in terms of transactional or analytical usage. Miller and Mork (2013) introduce the idea of a data value chain and differentiate three ways of data interaction, i.e. (1) data discovery subsuming activities of collecting, inventorying and preparing data, (2) data integration referring to activities of combining disparate data, and (3) data exploitation with respect to analytics allowing for insight generation. Taking an IoT-centric perspective, Borgia (2014) presents similar categories by differentiating the three consecutive phases of collection, transmission and process, and management and utilization. Considering these data frameworks, we identified five types of data treatment: Data *collection* refers to the generation of data and further includes the accumulation of data from different sources (e.g. Smart Dust). Data *aggregation* stores, manages, aggregates, and/or integrates formerly unstructured data. Enterprise Taxonomy and Ontology Management is one example for this characteristic as it supports structured data presentation. Data *analysis* provides techniques to assemble, exploit and interpret data on the basis of an underlying logic. Smart Advisors, for instance, advise users about the state of operations and furthermore support decision making by giving recommendations. Data *transmission* focuses on the exchange of data among involved entities. In this way, Wi-Fi networks like 802.11ax raise the data transmission rate and simultaneously support an ever larger number of devices. Lastly, data *execution* refers to the transactional usage of data

(Püschel et al. 2016). This characteristic subsumes DTs that are triggered on the basis of instructions and thus execute commands. 4D Printing, for example, executes the printing of a specific product on the basis of transactional data received in advance. As most emerging DTs handle data in more than one specific way, this dimension allows for non-exclusive characteristics. Smart Advisors, e.g. comprise the collection, analysis, and transmission of data.

As every interaction or operation involves the exchange of data, we consider DTs to have a data input as well as a data output, whereas the respective type of the data can assume different states. Depending on the considered DT, this characteristic is either of *digital* (also including “non-digital” forms of computing such as Quantum Computing) or *physical* nature. Virtual Reality, for example, transforms digital data into a physically perceptible 3D environment, surrounding its user. Smart Dust, on the other hand, scans the physical environment and generates digital data for further purposes. As combinations of characteristics are observable, e.g. for the IoT, we declared this dimension to be non-exclusive.

4.4 Service layer

As services are a ubiquitous phenomenon appearing in various contexts, there is no universally accepted definition across the disciplines of service research (Alter, 2012; Rai and Sambamurthy, 2006; Spohrer and Maglio, 2008). Taking a DT-centric perspective, we follow Arthur (2009) and understand service as a DT’s usage by (*human involvement*) and its purpose for humans.

In our taxonomy, human involvement is conceptualised as the way how humans use DTs. An *active usage* refers to humans who draw added value directly from the DT’s utilization. With HMI technology being part of an increasing number of devices, the idea of active usage applies to most examined DTs from our sample, e.g. Wearables. *Passive usage*, in contrast, means that humans are not in direct contact with a DT and that interaction is carried out by intermediary technologies. Typically network structures or hardware, such as 802.11ax and Neuromorphic Hardware, remain largely invisible for the user. When revising our taxonomy based on the feedback of our focus group meetings in the third iteration, the idea of including humans as the main user of DTs evolved. After discussing this suggestion with other researchers, we decided to add this dimension to our taxonomy, emphasising the role of the human and accounting for the trend towards HMI-supported DTs.

The main principle reflects the idea of Arthur (2009) and Ferré (1988), according to which every technology serves distinct purposes. A purpose-oriented view is suitable for distinguishing DTs, as it complements the rather technical view on technologies. Only in this way, the reason of existence of DTs can be fully understood. To do so, our taxonomy initially included six characteristics within a dimension called ‘main principle’. When classifying DTs, however, we recognised that a DT’s characteristics for the ‘main principle’ dimension are a good indicator for its characteristics related to the other dimensions. Accordingly, we abandoned this dimension, but strived for higher-level insights by means of archetypes.

5 Digital Technology Archetypes

To derive higher-level insights into DTs, we applied a cluster analysis to group 45 real-life objects from the GHC with regard to commonly occurring characteristics. In this way, we identified seven DT archetypes: *platform*, *connectivity*, *actor-based product*, *sensor-based data collection*, *analytical insight generation*, *analytical interaction*, and *augmented interaction*. Compared to the initially determined characteristics of the abandoned dimension ‘main principle’, these archetypes show a high degree of convergence concerning common characteristics.

In literature, dendrograms are often used to illustrate the results of hierarchical clustering. The tree-like structure provides information on how strongly the clusters correlate and how clusters developed during the execution of the chosen clustering algorithm. The first split in our dendrogram, which divides our sample of 45 DTs into two clusters, shows the highest distance and the lowest correlation between the grouped objects among all splits. Thereby, one cluster includes the archetypes platform and connectivity, sharing the infrastructure characteristic in the dimension ‘role of technology’. The other cluster covers the ‘application’ characteristic of the same dimension and includes the five remaining archetypes.

A further split divides the 'application' cluster into real-world oriented, i.e. actor-based products and sensor-based data collection, and service-oriented clusters, i.e. analytical insight generation, analytical interaction, and augmented interaction. Again, we observed significant distance measures and correlations among the occurring sub-clusters. The real-world orientated clusters encompass sensors and actors, sharing the collection and execution of data as common characteristic, whereas service oriented clusters heavily rely on data analytics and transmission as common characteristics. Below, we present short descriptions of the identified archetypes and provide additional statistical analysis in Figure 4. For each dimension, we show the characteristic which occurs most frequently.

			Service	Content			Network		Device		
		Relative Frequency	Human Involvement	Data Treatment	Input	Output	Multiplicity	Direction	Role of Technology	Scope	Examples
Archetypes	Platform	11%	Active Usage (100%)	Transmission (100%)	Digital (100%)	Digital (100%)	One-to-Many (100%)	Bi-Directional (100%)	Infrastructure (100%)	Cyber (100%)	Serverless PasS, Hybrid Cloud Computing
	Connectivity	18%	Passive Usage (88%)	Transmission (100%)	Digital (100%)	Digital (100%)	Many-to-Many (63%)	Bi-Directional (100%)	Infrastructure (100%)	Cyber (88%)	Blockchain, 802.11ax
	Actor-based Product	13%	Active Usage (100%)	Execution (100%)	Digital (100%)	Physical (100%)	One-to-One (100%)	Uni-Directional (100%)	Application (100%)	Cyber-Physical (100%)	Autonomous Vehicles, 4D Printing,
	Sensor-based Data Collection	9%	Active Usage (100%)	Collection (100%)	Physical (100%)	Digital (80%)	One-to-One (100%)	Uni-Directional (100%)	Application (100%)	Cyber-Physical (100%)	Bioacoustic Sensing, Smart Dust
	Analytical Insight Generation	11%	Active Usage (100%)	Analysis (80%)	Digital (100%)	Digital (100%)	One-to-One (100%)	Bi-Directional (80%)	Application (100%)	Cyber (100%)	Citizen Data Science, Machine Learning
	Analytical Interaction	18%	Active Usage (100%)	Transmission (88%)	Digital (100%)	Physical (100%)	One-to-One (100%)	Bi-Directional (100%)	Application (100%)	Cyber-Physical (100%)	Virtual Assistant, Smart Advisor
	Augmented Interaction	20%	Active Usage (100%)	Collection (100%)	Physical (100%)	Digital (56%)	One-to-One (100%)	Bi-Directional (100%)	Application (100%)	Cyber-Physical (100%)	Gesture Control, NLQA

Figure 4. Archetypes of 45 Digital Technologies from the Gartner Hype Cycle

As outlined, two archetypes serve as infrastructure for other DTs and together represent one third of the examined DTs. On the one hand, *platforms* are used to facilitate the location-independent accessibility of formerly discrete data from a single source. Serving as a hub that connects several entities, platforms especially differ from other network structures in terms of their multiplicity. The *connectivity* archetype, in contrast, is enabled or enhanced by DTs that focus on efficient data throughput. Unlike platforms, this archetype is characterised by a passive form of usage, whereby DTs remain largely invisible for users. Regarding the cluster of application-oriented DTs, two archetypes incorporate devices directly supporting the execution of the DTs' functionalities. First, *actor-based products* have a direct impact on our physical environment by improving the efficiency of activities in terms of speed, resource consumption, or cost. Accordingly, actor-based products are the only archetype exclusively characterised by data execution. All DTs related to the *sensor-based data collection* archetype share the constitutive characteristic of a uni-directional data flow, but differ in their purpose of collecting data from various sources. To gather information, this archetype uses sensors and is thus characterised by digital data input. Altogether, actor- and sensor-based DTs constitute 22% of our sample. The cluster of application-oriented DTs further differs between three service-oriented archetypes and accounts for half of the examined DTs. Mainly referring to information processing, *analytical insight generation* supports knowledge creation and decision-making. As this archetype has a cyber focus, it processes digital input and digital output via machine learning and artificial intelligence techniques. *Analytical interaction*, in contrast, focuses on analysing data and transmitting information into the physical world. Whereas the input data is digital, related DTs create output of a physical form. Finally, *augmented interaction* goes one step further by allowing for physical input. Mainly focusing on the collection and transmission of received data, this archetype primary embodies interaction capabilities without deeper analytical capabilities.

To evaluate the usefulness of the derived archetypes, we applied the Q-sort method. Two co-authors not yet familiar with the clustering results achieved an overall hit ratio of 84% (Moore and Benbasat, 1991) and a Cohen's Kappa Coefficient of 82% (Cohen, 1960). According to Landis and Koch (1977), these results reflect almost perfect agreement. Indicating the extent to which the DTs from our sample are correctly classified, the archetype-specific hit ratios amounted to at least 71% and an overall average of 85%, which is significantly higher than for a random sorting.

6 Evaluation and Application

After completing the development process, we evaluated our taxonomy as follows: first, we assessed the reliability and usefulness of our taxonomy by classifying DTs and by calculating related object- and dimension-specific hit ratios. Second, we offer initial insights into the taxonomy's layers and illustrate absolute and relative ratios for each characteristic.

To evaluate the taxonomy's reliability, two co-authors independently classified the sample of 45 DTs. Thereby, they achieved dimension-specific hit ratios of at least 82%. Moreover, 85% of the object-specific hit ratios exceeded 75%. These results corroborate our taxonomy's ability to provide in-depth insights into the nature of DTs. Nevertheless, the evaluation also revealed that an appropriate classification heavily depends on the amount of available information as well as on insights into the functioning of DTs. As our classification is based on definitions from the GHC, we ensured standardised information and content, but also limited ourselves to a single source.

To demonstrate the practical applicability of our taxonomy, we illustrate the example of NLQA. This DT allows users to ask questions in plain language which can be meaningfully answered by a computer or software service (GHC 2016). As an augmented interaction DT, NLQA is actively used by humans and thus an application-oriented DT with cyber-physical scope. Thereby, it collects acoustic data in form of speech, analyses these data regarding the underlying question, infers an appropriate answer, and subsequently transfers the answer to the interacting human. Hence, the input and output is physical, or rather acoustic. The interaction is characterised by a bi-directional information flow between both involved entities, namely NLQA and human.

In addition to the taxonomy's reliability and applicability, our classification results revealed initial insights regarding the taxonomy's dimensions and characteristics. Beyond the presentation of major highlights, we are happy to provide the detailed classification results upon request, which would exceed the scope of this study. Figure 5 shows an overview of relative and absolute ratios for all characteristics.

LAYER	DIMENSION	CHARACTERISTIC					EXCLUSIVITY
Service	Human Involvement	Active Usage (84%)	Passive Usage (16%)				ME
Content	Data Treatment	Collection (53%) [26%]	Aggregation (16%) [8%]	Analysis (53%) [26%]	Execution (16%) [8%]	Transmission (67%) [32%]	NE
	Input	Digital (76%) [67%]	Physical (38%) [33%]				NE
	Output	Digital (71%) [62%]	Physical (44%) [38%]				NE
Network	Multiplicity	One-to-One (76%)	One-to-Many (13%)	Many-to-Many (11%)			ME
	Direction	Uni-directional (24%)	Bi-directional (76%)				ME
Device	Role of Technology	Application (71%)	Infrastructure (29%)				ME
	Scope	Cyber (38%)	Cyber-Physical (62%)				ME

(…): absolute ratio [...]: relative ratio

Figure 5. Classification Results of 45 Digital Technologies from the Gartner Hype Cycle

Starting with the *service layer*, we found that humans actively use the capabilities of DTs in 84% of all investigated cases. This finding complies with the trend toward interaction and communication technologies such as NLQA, increasingly merging the physical with the digital world. The minority of DTs is hidden from users, however, network structures and hardware, e.g. 802.11ax, can support a high number of devices or applications. Regarding the *content layer*, it can be seen that data aggregation always appears in combination with the more frequently appearing activities data analysis and data transmission. The same holds for data collection, which occurs comparatively often (53%), but never as a single activity within this dimension. Data analysis (53%) and transmission (67%) are the most frequently occurring forms of data treatment. Regarding the input and output, only 15% of the DTs under investigation actually have digital input and output, mainly including wireless networks and infrastructures.

Further, only 4% feature physical input and output, e.g. NLQA. The remaining 81% describe hybrid forms of receiving and providing digital and physical data. On the *network layer*, 76% of the examined DTs enable bi-directional interaction among the involved entities, which is another indicator for increased connectivity and use of HMIs. Referring to the multiplicity dimension, our sample stresses the fact that only 13% of the investigated DTs participate in one-to-many and only 11% in many-to-many interactions. Again, platform and connectivity technologies connect multiple objects. The most common interaction pattern is to be found in a one-to-one (76%) connection. Further, the assessment of the *device layer* revealed that 71% of the classified DTs are application-oriented. This high percentage accounts for the increasing dissemination and modularisation of services, being not determined to use one specific hardware or device. Besides, more than half the sample have a cyber-physical focus (62%). The use and further development of sensor, actor, and HMI technology might be a possible explanation for this. All in all, we observed a high number of interaction and communication features which are to the most part realised through device-independent services with a focus on bi-directional interaction with humans.

7 Conclusion

Considering the tremendous importance of DTs in the digital age, we proposed a multi-layer taxonomy that enables the classification of individual DTs. Thereby, we only investigated DTs that can be delimited from both comprehensive concepts such as smart home and from physical components such as volumetric displays. Our taxonomy characterises DTs with respect to eight dimensions structured along the layers of extant DT architectures, i.e. service, content, network, and device. To demonstrate the taxonomy's usefulness and applicability, we classified 45 DTs from the GHCs of the last three years (Gartner Inc., 2015, 2016, 2017a). We also applied cluster analysis to derive higher-level insights and identified seven DT archetypes each of which represents a distinct typical combination of characteristics from our taxonomy. These archetypes are: platform, connectivity, actor-based product, sensor-based data collection, analytical insight generation, analytical interaction, and augmented interaction.

As any research project, our taxonomy and archetypes are beset with limitations that stimulate future research. First, DTs are a fast-moving field. This field will face the emergence of countless DTs with novel functionalities in the near future. We accounted for this circumstance by initiating the taxonomy development process with a conceptual-to-empirical iteration (Nickerson et al., 2013), preparing our taxonomy for being adaptable. Nevertheless, our taxonomy should be subject to repeated adjustment and re-evaluation. Second, the classification and clustering process was limited to a sample of 45 DTs. Therefore, the taxonomy will benefit from validating further DTs. In particular, the comparison with previous hype cycles will reveal insights about how DTs have developed over time. To reduce potential bias, we also recommend including sources beyond the GHC.

Apart from these limitations, our results are a first step towards an understanding of the nature of DTs. So far, the fast-changing field of DTs lacked a clear definition of the term and associated characteristics, which is the substantial transformative potential of DTs could not yet be fully tapped. By offering theoretically and empirically well-founded insights, our work adds to descriptive knowledge in this field. Our taxonomy serves as an analytical lens for DT providers. It also enables DT users (i.e. managers and product designers) to make informed decisions on the adoption of distinct technologies, e.g. by comparing DTs in terms of their characteristics or by reasoning about DTs in terms of our archetypes. Further, our archetypes enable the identification and comparison of substitutable technologies, which helps reduce an organization's uncertainty of technology selection. We hope that our results encourage researchers and practitioners to join our attempt to shed light on this highly relevant field and to fully tap the economic and societal potential of DTs.

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